

ROLE OF WALMART FULFILMENT MANAGEMENT SERVICES IN OMNI CHANNEL RETAILING USING MULTI-DEPOT VEHICLE ROUTING MECHANISM

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Abstract – The challenge to develop innovative FF solutions for online orders has rapidly grown into a huge challenge for brick-and-mortar retailers. Pure online players have increasingly been able to challenge them on in-store sales, and the advantage of focusing purely on in-store sales is no longer sustainable. Retailers are in a perpetual quest for new methods of fulfilling online orders and arranging last-mile logistics. Lead-time reduction, in this case, has become an important requirement. Of the newest approaches for doing so, the OC approach via using already existing infrastructure, by incorporating DCs and local stores into one FF system is among others. Therefore, this paper introduces the fast integrated order FF concept in grocery retailing and meets new challenges arising from this development. Empirical analysis yields cost items pertinent to decisions regarding order processing in a store, and a procedure for computing total FF costs is constructed. The policy involves allocating orders to different depots and determining routes at each of these depots as a function of their particular FF costs. A specially designed cluster-first, route-second heuristic is applied. The results indicate that the integrated rapid order FF saves approximately 7.4% of costs over a DC-based FF. However, because the in-store order processing will still be the key cost factor, this does not mean that DCs will be entirely substituted with store-based FF. All these results reflect the need for modeling the in-store processing costs much more precisely when deciding FF over a diverse network.

Keywords – Omni Channel Retailing, Walmart, Multi-Depot, Combined Instant Order Fulfilment, Same-Day Delivery, Transport Routing.

1. INTRODUCTION

More and more B-n-M retailers are now beginning to merge their offline traditional sales channels with online ones, becoming "Omni-channel" retail players. With this strategy, customers can shop through a perfectly unified platform using the chain's different outlets of physical stores. The larger e-commerce grows, the more the retailers' aim is focused on increasing customer value as a result of having a good shopping experience and high sales [1]. To do this, they are repositioning supply chain activities so that they are customer-facing and agile enough to rapidly respond to

demand coming in from anywhere in the network-meaning from the distribution centers all the way down to the retail store. Physical retailers for OC, meanwhile, are increasing their utilization of store locations as local inventory points for shipping out orders captured online. This now results in those same products on traditional B-n-M shelves and in backroom storage being utilized not only to serve the local customers in stores but also to fulfil and ship online orders direct from the stores. This is referred to as "ship-from-store" (SFS) and affords the retailer the ability to expand with minimal additional investment in the underlying logistics structure, particularly in dense urban markets.

Retailers such as Walmart have already deployed in-store e-commerce FF models. While bigger DCs exploit economies of scale, stores add the benefit of being closer to customers. Recent empirical studies have only gone conceptual without identifying the specifics [2]. What lacks in the approach remains a holistic cost assessment and optimization methodology that focuses on using stores as picking points and shipment points as well. For this reason, having accurate analysis and modeling of in-store processing costs is essential to making defensible choices about FF and order assignment between stores and DCs. The majority of modeling technique literature has either concentrated on operational FF or the strategic design of OC networks that include stores, ignoring the finer points of order-specific shipping and service cost calculations [3]. Customer expectations have increased while the operational challenges in the cities have amplified, especially with this rise of delivery services that promise two hours or less for FF. FF is the main cost driver in urban supply chains, as high population density and the complexities involved in logistics make last-mile delivery a complicated affair.

While these rapid delivery services are important for reacting to customer expectations and positioning between competitors, they add significantly to the cost of filling online orders [4]. Furthermore, the layout of a traditional

store is not designed to allow for optimal inventory management or picking of orders that contribute to increased picking costs and stock-outs from simultaneous demand of customers arriving both online and in the walk-in END. Simplifying said, OC retailers should weigh the need for quick high-quality FF services against the costs generated by such a strategy. By SFS strategies, retailers can get themselves closer to their customers at the same time enhance sales, reduce delivery times, and raise margins. A miscalculation in implementing the SFS strategy has left retailers in the face of a host of problems, and among them, stock shortages both in online and offline channels and increased cost, lost sales, and customer dissatisfaction. This underlines the basic point that order FF and last-mile delivery do much in the strategic planning of OC retailing [5], [11].

Motivation:

Walmart FF Management Services are the faces of change in OC retailing. Consumers are getting more and more comfortable with purchasing through e-commerce websites, and their expectations are heightened; therefore, their purchase journey should be streamlined and offered to them through an in-store experience. By maintaining a wider store and distribution network, Walmart benefits from localized inventory and optimizes delivery at the last mile for faster and more efficient FF. This integration does boost satisfaction around delivery options but supports inventory management by utilizing the infrastructure more. In this sense, the handling by Walmart exemplifies how a traditional retailer may innovate and survive the competitive fields, in this case marked by increasingly high competition, especially from pure online companies.

The major contributions of the developed framework are depicted as follows:

- Empirical analysis is used to identify and gather expenses that are relevant to decisions. This entailed working with a major European grocery retailer to analyze how orders are processed in stores based on location and basket.
- A unique decision problem involving assigning orders to pick up sites (DCs) and stores) and setting up delivery tours incorporates the cost parameters gathered for order processing in OC operations.
- To maximize short-term delivery lead times for attended home deliveries, a decision model incorporating the location-assignment problem with the multi-depot vehicle routing problem (MDVRP) is developed.
- To tackle the practical implementation of this concept, a specific heuristic is created that employs a cluster-first-route-second methodology, enabling more effective order FF and routing.

2. LITERATURE SURVEY

Dethlefs et al. [6] introduced the concept of rapid integrated order FF in grocery retail, thereby introducing new challenges in the domain. Decision-relevant costs of in-store order processing are empirically determined as an approach

to evaluate the overall FF cost. The problem focused on the assignment of orders to diverse depots and the optimization of vehicle routing for each depot considering depot-specific FF costs. An elaborated heuristic was used in order to solve the problem. The integrated rapid order FF approach incurred a smaller cost cutback compared to fulfilling the orders directly from the DCs. It concluded that the modeling of in-store order-processing costs would be critical to enable informed FF decisions through heterogeneous networks. Yet, this approach does carry a notable drawback, which is the oversimplification of store capacities and variability in demand, which could severely limit its application in a more dynamic or unpredictable setting.

Difrancesco et al. [7] defined the best-in-class configuration of in-store FF processes for online orders in an OC marketing atmosphere. Using a combination of exploratory modeling and a simulation-based approach, the best FF policies were determined by taking into account the various sources of uncertainty. To illustrate the usefulness and practical relevance of the approach, a case study was carried out utilizing actual data from a sport-fashion firm based in New York City. The result suggests the following: (i) The best time to batch online orders before beginning in-store picking; (ii) The best time to pick orders in transit so that delivery may begin; (iii) The quantity of pickers; and (iv) The quantity of packers, together with performance indicators related to each. However, its dependence on static assumptions about the retail operational environment might not capture the complexity or the dynamic nature that characterizes real-world retail settings.

Yang et al. [8] considered the effect of hybrid-FF OC strategies, like BOPS-STS and BOSS-BOPS-STS, for a retailer's store operations. The model was developed with the retailer operating both physical stores and online channels while serving two customer segments: those using fixed channels and OC-type customers. It was found that BOPS-STS and BOSS-BOPS-STS would shift the customer's FF preference for a time-insensitive or experience-based product provided that the hassle cost of pickup was low. In addition, both strategies expanded markets for time-sensitive or experience products. The critique is that the study made an assumption about static customer behavior, where the preference of the customer is taken as constant in nature, which also denies the volatile nature of customer preferences as well as external factors that would influence the actual performance of mixed OC strategies.

Two transitions in a manufacturing company's distribution channels toward retail customers are presented by Wan et al. [9]: the first is from a single-DC to a dual-DC system, and the second is from single-DC toward factory-direct distribution. For the three distribution channels, three equations were created inside a difference-in-difference framework to negotiate the differences between order FF and related costs. These were then utilized, along with private data on purchase history and delivery records, to figure out the implications of the three channels on order FF. The quantitative findings below provide an overview of the effects of the several channels on order FF. When compared to other distribution channels, the dual-DC channel demonstrated a decrease in lead time and an increase in fill

rate. However, the limitation of this approach lies in the assumption of consistent demand in all distribution models; hence it is unlikely for fluctuating demands due to seasonal fluctuations, etc.

Mou et al. [10] developed the bi-objective mixed-integer non-linear optimization model for order batching and assignment. The model's goals were to reduce individual hours, consequences for being early or late, and imbalances in workload. In an OC supermarket scenario, PF solutions were found using a GA-based heuristic. The model has been tested, indicating both the model's efficacy and the conflicts between ideals. Extensive numerical experiments were carried out to examine how specific operation characteristics at OC stores-the heterogeneity of the workforce and the crowding of the store-affected the efficacy of in-store order FF. The results revealed that the model was relatively robust with respect to the heterogeneity of the workforce but that coordination between online and offline traffic during peak times should be given significant attention. The method has a weakness, because the static evaluation of workforce attributes and crowding conditions hardly reflect reality due to the dynamic features of real-world supermarket environments.

2.1. Problem Statement

Despite the advantages of Walmart's FF Management Services, challenges remain in effectively integrating these services into a cohesive OC strategy. Issues such as fluctuating customer demand, inventory discrepancies between online and physical stores, and the complexities of managing logistics across multiple channels can hinder operational efficiency. Furthermore, the rapid pace of technological advancements and changing consumer preferences necessitate continuous adaptation of FF processes. Consequently, the effectiveness of Walmart's FF strategy must be evaluated to identify potential gaps and optimize its operations, ensuring that the company can meet evolving customer expectations while maintaining profitability in an increasingly competitive environment.

3. PROPOSED METHODOLOGY

In this scenario, reduction of lead time has become increasingly critical. One of the newest approaches is the OC approach by using existing infrastructure by incorporating DCs and local stores into a single FF system. This paper introduces the concept of fast integrated order FF in grocery trading and meets new challenges arising from this development. Empirical analysis led to cost items relevant to decisions about in-store order processing, and a method for evaluating overall FF costs is developed. This strategy comprised order assignment to various workshops and designing vehicle routes for each workshop based on their specific FF costs. An especially designed cluster-first, route-second heuristic (CFRS) is used.

3.1. Time and Motion Study in Store Order Process

The allocation of orders to specific locations is largely influenced by the costs associated with processing orders in stores. Since store-based FF is a relatively new concept, it is important to investigate the picking systems and the costs

involved. This approach focuses on in-store picking within the customer areas, aiming to propose a solution that requires minimal operation effort and only negligible modifications to the existing store layout.

3.1.1. Process Overview and Accomplishments

The selection, packaging, and shipping time frames for store-based FF were investigated in this study. Purchases picked at stores, in contrast to DCs, are usually not able to be batched because of space constraints in the backroom for sorting, significant variations in customer orders, and stringent lead times. Furthermore, retailers place a higher priority on reducing disturbances to consumers while they are in-store, which makes single-order picking more practical than batch picking, which calls for larger trolleys. As a result, selecting is done for each booked order individually. The picker makes a route plan to quickly collect all necessary things after starting with an inventory list arranged by genre and unit position. After selecting all the items, the picker goes back to the backroom and packs them into uniform shipping boxes. These crates are delivered to the agreed-upon handover location.

While the overall FF process in stores resembles that in DCs, the detailed steps and times differ significantly due to the store layout, which is designed for product display and customer interaction rather than optimized picking efficiency. The differences stem from factors such as customer interactions, the inability to organize products in zones, limited process automation, and restrictions on technological tools to avoid disturbing customers. Store-based FF is viable only if the volume of online orders remains below 10% of the store's total volume, which aligns with the arcade segment for express conveyances. In this scenario, the budgets associated with processing in stores become critical, as replenishment follows the same delivery patterns, regardless of whether additional online orders are handled.

3.1.2. Examined Structures and Accomplishments

In the subsequent sections, the structural characteristics of in-store processes and the resulting cost dependencies will be derived.

- **Process Phase:** Three primary stages were identified during the time and motion analysis. These stages, referred to as item retrieval time, packaging time, and dispatch preparation time, collectively contribute to the total order handling duration.
- **Item Retrieval Time:** The item retrieval procedure consists of three independent stages: (i) purchase receipt, packing list generation, and retrieval preparation; (ii) product location and selection; and (iii) product category switching. Since each order is chosen separately, there is a defined setup time for each order during the (i) setup phase. Every store and order are different when it comes to preparatory time, which includes things like starting up and getting from the warehouse to the purchasing floor. When the purchaser hits a chosen shelf, the product search procedure is the primary factor that

determines the total retrieval time (ii). Search time is influenced by the quantity of items in every segment and rises in densely packed areas (e.g., multiple products with little shelf space). Every product has a designated category. There is a modest decrease in seeking time per commodity when more goods from just one group are included in an order, according to empirical data. (iii) Depending on the total quantity of genres per purchase and the travel distance in the store between them, moving between genre locations requires moving across various shelves.

Retrieval times therefore differ for every client order and retailer which results in retrieval fees that are particular to each order. The computation of retrieval costs involves multiplying the duration by the hourly rate of an in-store gatherer. The picker goes to the wrapping platform, which is already taken care of as a component of the container's procedure, after retrieving the items. Our empirical research indicates that supermarket stores usually package their products using standardized boxes. Since every item fit into these boxes, the amount of packaging required depends on the size of the order and the policies of the particular retailer. Adjustments for product measurements, product handling needs (frozen goods, for example), and store layout are reflected in these operations. Determined total packing time is translated into packaging expenses. The amount of time spent processing an order prior to dispatch is known as deployment preparation time. No matter the quantity of items is ordered, loading time only happens once for each customer order, in contrast to recovery and wrapping. As a result, loading charges are determined based on the particular shipment.

In summary, our findings indicate that the primary factors influencing total order handling time are order size, the number of items, and the number of product categories within an order. Additionally, the layout and operational processes of the store play a crucial role in determining the time required for item retrieval. This leads to a unique handling time for each customer order, varying by store. The overall duration is referred to as order handling time, encompassing all steps involved in retrieval, packaging, and dispatch preparation. The amount of time needed in a store to process a certain order is indicated as such. The associated order handling expenses are computed through incorporating the in-store picker's hourly compensation rate. The following part will expand on this model, which somewhat depends on the determined order expenses for handling and the interrelated factors that go along with them. The total of order-specific handling costs (for dispatch preparation) and specific to the item managing expenses (for recovery and wrapping) determines these processing expenses.

3.2. System Model and Solution Framework

This section outlines the variant of the multi-depot vehicle routing problem (MDVRP) and describes the developed solution methodology. Given the focus on short turnaround times, the application is referred to as Rapid Integrated Order FF (RIOFF). Together, the proposed model

is termed as MDVRP with rapid integrated order FF (MDVRP-RIOFF).

3.2.1. System Model

The model identifies dispatch locations from a group consisting of both retail stores and distribution centers (DCs). The term "depots" will be used to refer to both stores and DCs collectively. All customer and depot sites are encompassed within the location set.

- **Cost parameters.** The foundation of assigning orders to workshops and determining vehicle directions lies in (i) the costs of processing orders at each locality and (ii) the corresponding conveyance expenses. All cost details are known beforehand and are factored into the optimization process. Consequently, these two cost factors are precomputed and used as input for the model. Using these predetermined cost components, the MDVRP_RIOFF is formulated to assign customer orders to depots and establish the relevant vehicle paths.
- **Problem sets.** For an undirected, weighted network, a set of nodes is defined, which includes both depot locations and customer locations. This results in a total number of workshops and regulars. The connections between various localities are embodied by a set of links. The set of vehicles and a detachment of uniform vehicles accessible for delivery at each workshop are defined, meaning vehicle types may differ between depots.
- **Model parameters.** At each workshop, a standardized vehicle sets with a fixed capability for purchaser remits is presented. The exemplary operates within a specified delivery timeframe, where all orders must be processed. Each vehicle also has a restricted route length. All routes are assumed to follow the triangle dissimilarity, begin and end at the same workshop, and the total presented vehicles, v , are presumed to be sufficient to meet overall demand. The inventory allocation problem is resolved before the downstream order obligation and channeling process. Therefore, accessible merchandise stock does not be contingent on received online orders, and depots lacking certain items are excluded in the preprocessing stage. Additionally, it is assumed that the overall stock across workshops is adequate to fulfil all customer orders. Each workshop has a maximum order capacity it can handle and a minimum order threshold that must be allocated to it if selected for FF. The minutest threshold confirms competent use of resources, while the maximum reflects the labor capacity within the allotted timeframe.
- **Decision variables.** Two decision variables are utilized. The binary variable signifies whether a customer order is assigned to a workshop, represented as 0 or 1. The binary variable indicates whether a vehicle travels between two locations.

Finally, the auxiliary variable specifies whether a depot is used for fulfilling customer orders. Figure 1 illustrates the Framework of the developed model.

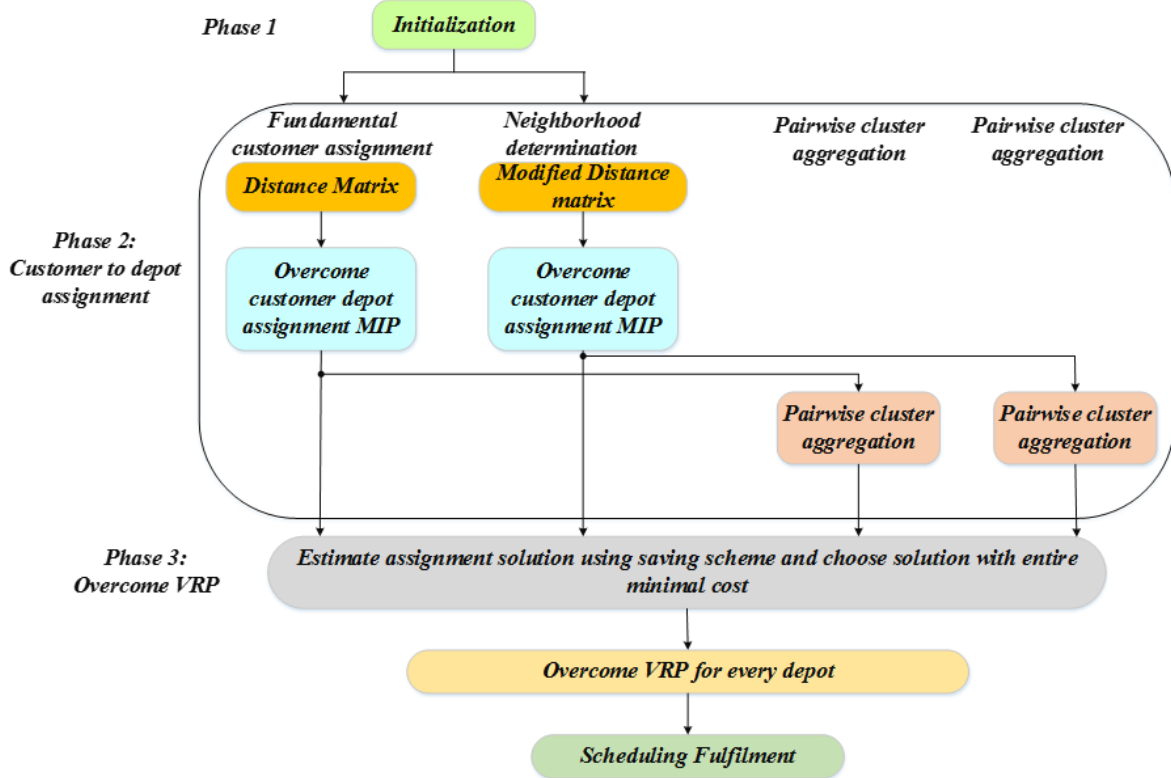


Figure 1. Framework of the developed framework

3.2.2. Solution Framework

The problem we address falls within the category of NP-hard problems as it merges two NP-hard components: a knapsack problem (i.e., assigning customers) and a variant of a MDVRP. Additionally, due to the very short lead times for orders (e.g., under one hour), computational time becomes a critical limitation. To tackle this, a CFRS heuristic is introduced, which efficiently solves the problem for scenarios requiring next-hour deliveries. The CFRS method is a widely recognized approach that has been applied successfully in various contexts. The core idea is to swiftly determine a achievable and operative customer-to-depot allocation based on an guesstimate of routing expenses, facilitating the identification of a cost-efficient solution for vehicle routing.

4. RESULTS AND DISCUSSION

This segment evaluates the effectiveness of the heuristic and the effects of incorporated order FF. The various data sets are generated to enhance the generalizability of our results. The locality data for regulars and retail outlets is based on an outsized metropolitan with an approximate population of 1.5 million and an area of about 400 km². Purchaser and workshop locations are consequent from geospatial data using OpenStreetMap, with a random subset selected for each scenario. Customers have basket sizes ranging from 1 to 50 products, with an average basket size of 30 products. On average, each order contains 3 units of a product. There are two types of depots: large depots, which

handle 20% of orders with a maximum capacity of 30 orders and 1000 products, and small depots, which handle 80% of orders with a maximum capacity of 10 orders and 500 products. The large depot can serve up to 5 customers per tour, while the small depot can serve up to 3. Processing and transportation costs vary slightly between the depots, with large depots incurring lower costs per product but higher transportation costs.

4.1. Assessing the effectiveness of the proposed method over conventional studies

This section depicts the effectiveness of the proposed method is examined via the graphical illustration over other solutions. The detailed analysis is encompassed below:

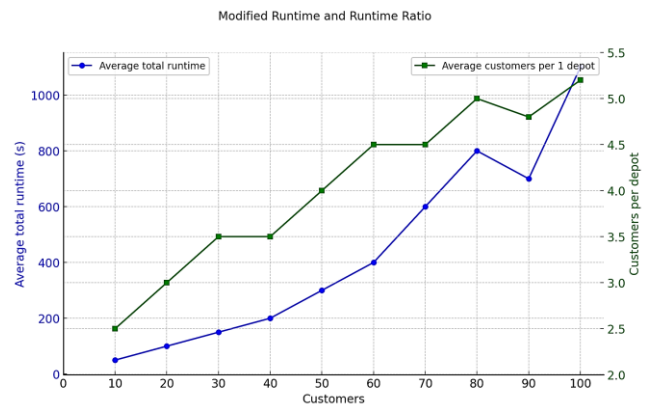


Figure 2. Analysis of Runtime and runtime ratio

Table 1. Experimental Outcomes of Average runtime and cost consumed on test data

C	Instan ces	Samples solved to optimality			Instan ces	Samples solved to optimality		
		Average Runtime		Cost Consumed		Average Runtime	Average gap to lower bound	Cost Consumed
		Gurobi	Proposed	Gurobi (%)		Proposed	Gurobi	Gurobi (%)
25	0	-	-	-	15	2.5	10.8k	3.5
20	1	1,820.6	0.7	1.11	14	3.5	10.8k	4.8
15	11	1,717.7	0.49	4.47	4	0.6	10.8k	7.07
10	15	36.7	0.43	5.94	0	-	-	-
5	15	0.2	0.17	0.87	0	-	-	-

Figure 2 depicts the Analysis of Runtime and runtime ratio. The average total runtime is represented by a blue line, while the average customers per depot is represented by a green line. The x-axis shows the number of customers, ranging from 0 to 100, and the two y-axes show the average total runtime (on the left) and the number of customers per depot (on the right). The graph indicates that as the number of customers increases, the total runtime rises steadily, particularly after 60 customers. There is also a gradual increase in the average number of customers served per depot, peaking around 100 customers, where each depot serves approximately 5 customers. An interesting dip occurs around 80 customers, where runtime increases but the number of customers per depot decreases momentarily, showing some non-linear behavior. Table 1 depicts the Experimental Outcomes of Average runtime and cost consumed on test data. The tabulation proves that the developed method outperforms well compared to other solutions.

5. CONCLUSION

This paper analyzes the circumstances under which rapid integrated order FF benefits the order FF process of OC retailers. It is the first application of a combined assignment and vehicle routing problem framework. A model deployed here is effective for retailers that aim at integrating their stores with online channels such that they may derive optimal FF designs and schedules. The costs relevant to the decision-making process concerning online order FF variety, especially differences in the costs of different depots, are identified. Store-specific costs are quantified in the empirical study and incorporated into the optimization approach in a structured manner. The main outcome of this is that the decision whether to fulfil at DCs or at stores is significantly influenced by the locations of the DCs and their respective cost structures. For example, RIOF by DCs makes sense only if such hubs are located near the customers in a manner that ensures critical order volume. In general, a hybrid model based on both DCs and stores for RIOFF generally yields a lower-cost resource chain associated with store-only or DC-only models. The approach can also be improved further to include the consideration of multiple periods so that a variety of time windows may be allowed in the selection process. This enhancement may mean that apart from the acceptance of fast delivery orders, there would also be the acceptance of orders for later delivery, with the optimization of vehicle and depot capacities and the balancing of the rates of inventory levels across locations. This availability of time windows is also very closely associated to appraising stratagems for

these delivery options. In fact, the model, currently assuming a fixed inventory level at stores, would be improved significantly if the optimal number of inventories per store could be determined in order to depend on online demand and replenishment cycles. Moreover, the improper or unpredictable fluctuations in demand or shrinkage in inventories, rapid changes in the items to be stocked within the inventory, and so on might all imply the need to include stochastic components.

CONFLICTS OF INTEREST

This paper has no conflict of interest for publishing.

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